Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org
© 2025 SCPE. Volume 26, Issues 2, pp. 907–915, DOI 10.12694/scpe.v26i2.4088

THE OPERATION AND MAINTENANCE STRATEGY OF SMART GRID BASED ON INTELLIGENT PERCEPTION AND OPTIMIZATION ALGORITHM

DEXIONG LI[*], JUNYI HUO[†], YU WANG[‡], JING LI[§], AND HUICHAO JIN[¶]

Abstract. Due to the existence of a sensor model, the state perception of the distribution network can obtain higher RMSE. Because of this situation, this topic intends to use artificial intelligence technology to realize the embedded sensing system of stable operation of distribution network: Front-end sensor and wireless inlet design. According to the stable operation characteristics of the distribution network, a stable data collection system is established. Various algorithms based on data unification and identification are proposed to sense calculation parameters. An adaptive dynamic stability detection method is designed based on a deep neural network. Experiments show that an RMSE of 0.031 can be obtained by this method. This method can realize the accurate perception of the running state of the distribution network.

Key words: Artificial intelligence; Distribution network; Stable operation; Embedded system; Behavior perception; Calculation parameter

1. Introduction. With the large-scale entry of new energy into the distribution network, the distribution network has gradually developed in the direction of active power supply. Active distribution network operation status monitoring is a vital link to improve. With the increasing complexity of the distribution network, the traditional static sensing method cannot meet future distribution network development requirements. The research shows that the stable state detection method of a dehumanized intelligent distribution network based on 3D Lidar is significant. Literature [1] proposes to adopt a combination of static and dynamic sensing modes to realize real-time monitoring of distribution network characteristics in real scenarios based on obtaining a complete panoramic distribution network modeling. Literature [2] obtains global status awareness based on feature monitoring data to improve maintenance and management efficiency. However, the detection effectiveness of this method is highly variable. Literature [3] studies different sensing methods according to different physical parameters to evaluate the proper degree of sensing results. In this way, the optimal sensing physical quantity is selected. Literature [4] intends to adopt sensing technology and integrate big data with 3D inspection to realize real-time monitoring of the environment. However, the scalability of this algorithm is not robust. The research shows that the new sensing technology of distribution networks based on real-time phase information has important theoretical significance and application value. In this paper, the observation equipment is set up in the distribution system, and the influence factors of its state are extracted. Then the collected data is analyzed by support vector machine algorithm. Finally, the data are analyzed using the extended and short-time memory network. Finally, a distributed sensor network based on artificial intelligence is constructed, and its operating state in the distribution network is studied.

2. Application of embedded sensing system in stable operation of distribution network.

2.1. System hardware design.

2.1.1. Front-end perceptron. CC2530 is used as the front-end sensor to consider network energy consumption and signal acceptance sensitivity [5]. Then, it realizes data interaction with the MCU I/O interface

[*]Department of Electrical Engineering, Shijiazhuang Institute of Railway Technology, Shijiazhuang 050041, China
[†]Department of Electrical Engineering, Shijiazhuang Institute of Railway Technology, Shijiazhuang 050041, China
[‡]Department of Electrical Engineering, Shijiazhuang Institute of Railway Technology, Shijiazhuang 050041, China
[§]Department of Electrical Engineering, Shijiazhuang Institute of Railway Technology, Shijiazhuang 050041, China
[¶]Department of Electrical Engineering, Shijiazhuang Institute of Railway Technology, Shijiazhuang 050041, China (Corresponding author, jhcmail@163.com)

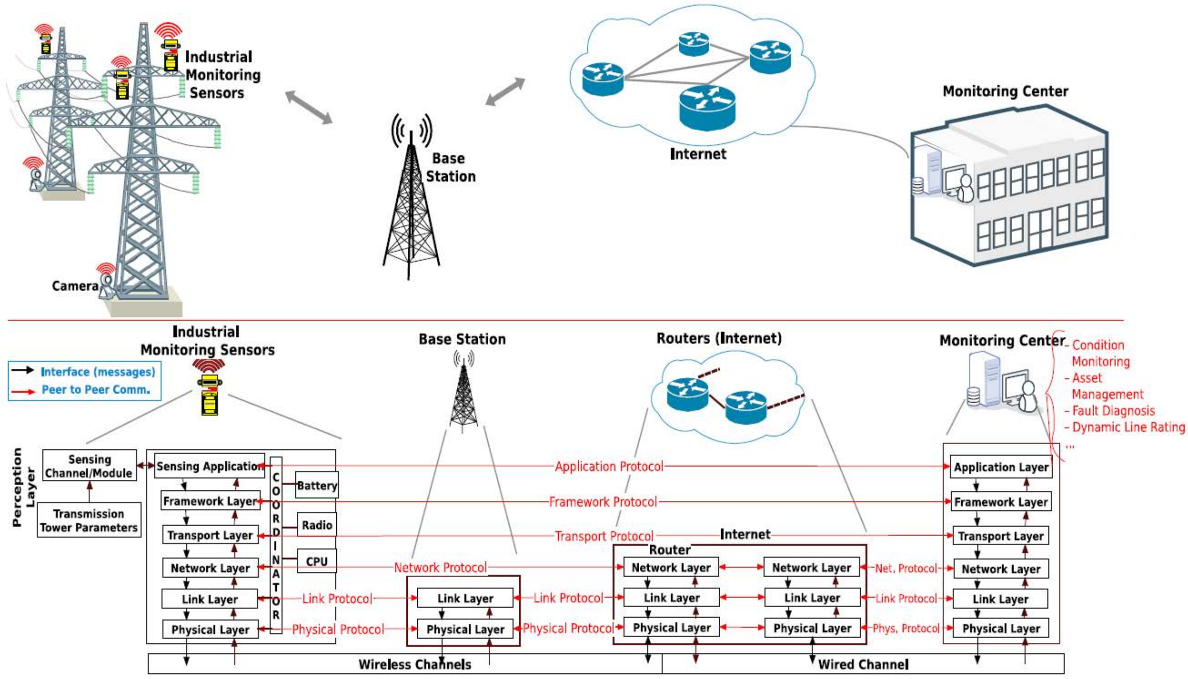


Fig. 2.1: *Hardware architecture of embedded sensing system gateway.*

through the CC2530 interface. Finally, the sensor, the wireless transceiver module, and the clock module constitute the entire system's front-end sensing module.

2.1.2. Implementation of Wireless Gateway. The implementation of a wireless gateway includes the functions of data transmission, encapsulation and analysis. The analysis of the S3C2440 microcontroller shows that it works at more than 400 MHz, which can fully meet the needs of the sensing field [6]. The module is combined with the TFT-LCD display, remote control button and other modules to realize the overall architecture of the wireless gateway (Figure 2.1). Install the LM25965-5.0 switching regulator on the gated power supply to enhance the stability of the gated application.

2.2. Software Design.

2.2.1. Establish a stable power network monitoring system. The stable state monitoring of the distribution network cannot be separated from a lot of data support [7]. This paper presents a data collection system for the operating state of the distribution network (Figure 2.2 cited in Water 2019, 11(3), 562). R is a data collector and Z is an encoder. H_1, H_2 is the length of the channel. This paper determines the information collected by each collector to ensure the completeness of data collection under a steady state [8]. The information collected is obtained using the coding function, and the input signal is generated. Select a point in time in the data acquisition construct in Figure 2.2. The data acquisition channel specification expression is:

$$A_v = B_{jv} + C_v, C_v \in N \tag{2.1}$$

B is an input signal. A is an output signal. v is a kind of acquisition time. m is the steady-state operating performance data collected for a distribution network. j is a specific data collection point. C is a disturbing noise. N is the variance. Set the critical capabilities of the channel to transmit information consistent with the minimum code transfer requirements [9]. The formula for calculating the upper bound of the channel is as

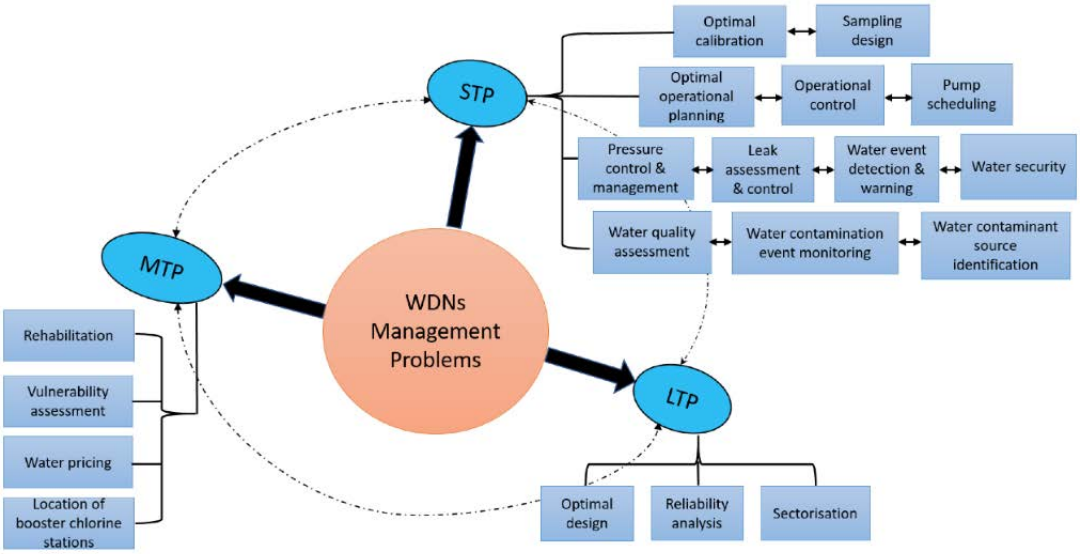


Fig. 2.2: *Distribution network operating status information collection architecture.*

follows:

$$W = H_1 \sum_{j}^{\pi} \log\left(1+\frac{\phi_j}{N_j}\right) + H_2\left[\log\left(1+\frac{\phi_g}{N_f}\right)+\log\left(1+\frac{\phi_c}{N_c}\right)\right] \tag{2.2}$$

W is the upper bound of the channel. ϕ_j, ϕ_g, ϕ_c is the average of the noise in the information transmission. N_j, N_g, N_c is the variance of noise in information transmission. For the analysis of each average noise power, the power limit of each information transmission stage can be obtained:

$$\begin{cases} \phi_j \geq \frac{1}{n}\sum_{i=1}^{n}\left[B_{j1}(\lambda, v)\right]^2 \\ \phi_g \geq \frac{1}{n}\sum_{i}^{n}\left(B_{12}, \cdots, B_{m2}, i\right)^2 \\ \phi_c \geq \frac{1}{n}\sum_{i}^{\pi} C_i^2 \end{cases} \tag{2.3}$$

λ is the number of facilities in the distribution network [10]. According to the restriction given in equation (2.3), the sampling interval of the front end is set under steady state, and the global acquisition of steady-state data is completed.

2.2.2. Extraction of calculation parameters of intelligent sensing. Data normalization and recognition methods are adopted based on the analysis of steady-state data collection of distribution networks [11]. Because the collected data are spatiotemporal dependent, a multi-level data consistency modeling method is proposed. For obtaining steady-state data, record each characteristic quantity and generate the following matrix:

$$S = \begin{bmatrix} s_{11} & \cdots & s_{1\pi} \\ \vdots & \ddots & \vdots \\ s_{71} & \cdots & s_{2\pi} \end{bmatrix} \tag{2.4}$$

S represents the acquisition matrix, and 5 represents a single property of the collected data. A is to get the number of columns and rows in the matrix.

$$\tilde{\lambda}_\pi = (\zeta_1, \zeta_2, \cdots, \zeta_\pi) \tag{2.5}$$

$\tilde{\lambda}$ is a stable data vector while ζ represents a matrix column vector. Because of the different static sampling frequencies, some sampling data is missing. This paper proposes a dynamic optimization algorithm based on time series to estimate the similarity of discrete sequences and then extend and compress them [12]. This ensures consistency of sequence size. Select a random column vector in the formula (2.5) as the reference vector. Euclidean distance operations are performed on other column vectors, resulting in several distance matrices:

$$P_i = \begin{bmatrix} U_{11} & \cdots & U_{1,} \\ \vdots & \ddots & \vdots \\ U_{71} & \cdots & U_{\pi} \end{bmatrix} \tag{2.6}$$

Where k is the column vector, P_k is the distance matrix, and U is the European distance. The distance matrix is deduced, generating several distance loss matrices [13]. In this way, the approximate calculation of the column vector is achieved:

$$\begin{gathered} \sigma = \begin{bmatrix} \varphi_{11} & \cdots & \varphi_{17} \\ \vdots & \ddots & \vdots \\ \varphi_{71} & \cdots & \varphi_{\pi} \end{bmatrix} \\ W = \{W_1, W_2, \cdots, W_7\} \end{gathered} \tag{2.7}$$

σ is a group of distance loss matrices, φ is a group of loss degrees, W is a group of optimally regulated sequences, and it is also a group of shortest methods [14]. The minimum vector spacing is ensured by adjusting the vector spacing in the steady state using the dynamic rules. PC.A method was used to evaluate the steady-state data and eliminate the redundant duplication. First, the spacing of the adjustment vectors is normalized to obtain a normalized matrix of the form:

$$L = \delta - \frac{\delta}{\gamma} \tag{2.8}$$

L stands for standardized matrix. $\mathcal{S}$ is the parameter data after spacing adjustment based on formula (2.9). The expression for covariance and uniformization is now obtained:

$$\begin{gathered} Y = \frac{1}{\gamma} L \\ \mathrm{sid}(Y)[G, Z, K] \end{gathered} \tag{2.9}$$

Y is the covariance matrix. svd is SVD. G, Z, K represents the matrix formed after decomposition. G is a dimensionality reduction matrix. The SVM algorithm is used to solve the intelligent sensing parameters of a single sampling point, and the likelihood function is derived by referring to the independent relationship between the observation points in the sampling point [15]. The intelligent detection and analysis of sensor data are realized based on the above content.

2.2.3. Construct the AI adaptive perception model. The embedded sensing system studied in this paper is based on artificial intelligence. A sensor network with independent intellectual property rights is established, combining the theory and method of machine learning [16]. The input and output of dynamic behavior are calculated, and the weights in the model are adjusted according to the obtained state information. The system consists of four levels. From the principle of sensing mode in Figure 2.3, it can be seen that the system consists of the current stable state of the distribution network and the period when the failure occurs. The input vector is represented as:

$$\omega(t) = (\omega_1(t), \omega_2(t), \cdots, \omega_2(t)) = \{\pi(t), \pi(t-1), \cdots, \pi[t - (\partial - 1)\tau]\} \tag{2.10}$$

The adaptive perceptual model transmits input-level information to the hidden layer of the algorithm. Then, it is calculated by several hider nodes to obtain:

$$s(t) = \frac{1}{1 + \alpha'} \tag{2.11}$$

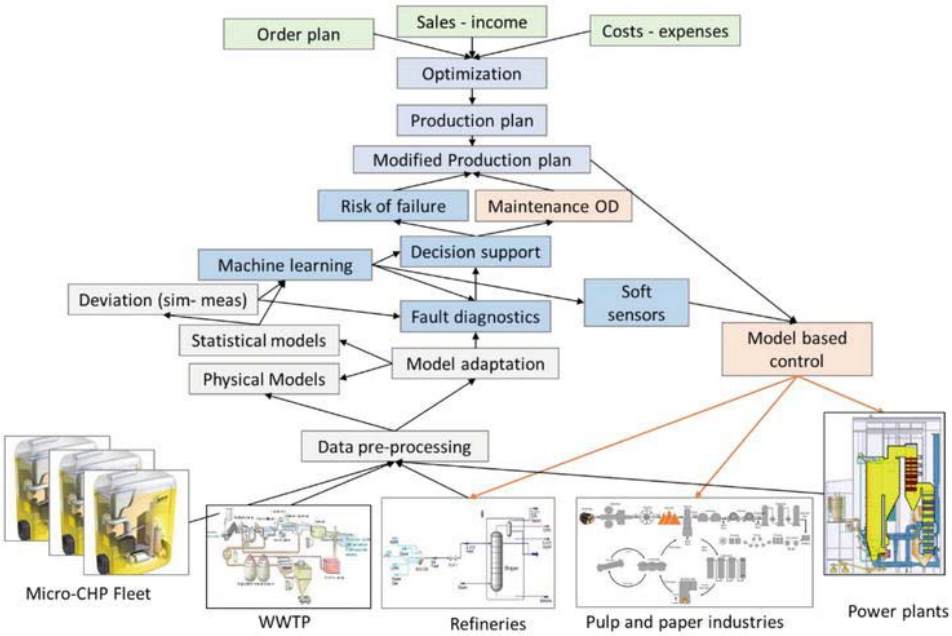


Fig. 2.3: *Adaptive perception model based on artificial intelligence.*

t is the output of the hidden layer, α is the constant, and r is the parameter weight. The Gaussian distribution characteristics of steady-state data are obtained by applying hidden layer measurements on a random layer [17]. This paper uses it to characterize the output characteristics of the system. The random layer's output result is expressed by solving each hidden node's Gaussian distribution.

$$\theta\left[\imath(t), r_0\right] = \frac{1}{1+\alpha^{\imath(t) r_0}} \tag{2.12}$$

Where θ is the output value of any layer, and r_0 is the weight of the implicit node parameter.

The reinforcement learning algorithm is introduced. The output of the random layer is studied in depth. It's expressed in one-dimensional Gaussian form [18]. Then, an adaptive learning method based on random stratification errors is adopted to realize state monitoring under dynamic conditions (FIG. 2.3).

2.3. Main Functional Components.

2.3.1. Data capture module. The information collected in today's intelligent distribution network includes current, voltage, frequency, temperature and other multi-dimensional information. Various sensors are added to the device, such as a phase measuring device, infrared sensor, ultrasonic sensor, etc. This new type of sensor can not only realize the online monitoring of the operation of the distribution network but also determine its position according to the specific accident or abnormal situation. A more complete view of power network operation can be obtained by fusing the signals collected by multiple sensors. In addition, real-time data is particularly critical in security situation awareness, so it needs to be quickly and accurately positioned. The solution uses high-speed technologies such as 5G, optical fiber communication or broadband power lines to ensure low delay and highly reliable data transmission. In addition, data synchronization is essential for multi-sensor or multi-location observation data. High-precision clock synchronization represented by GPS, IEEE1588, etc., can ensure the consistency of all data in time. This lays a good foundation for future multi-source information fusion and analysis.

2.3.2. Data processing and storage. The information processing module has become the system's core to ensure accurate operation. This project introduces Apache Spark technology into the distributed network to

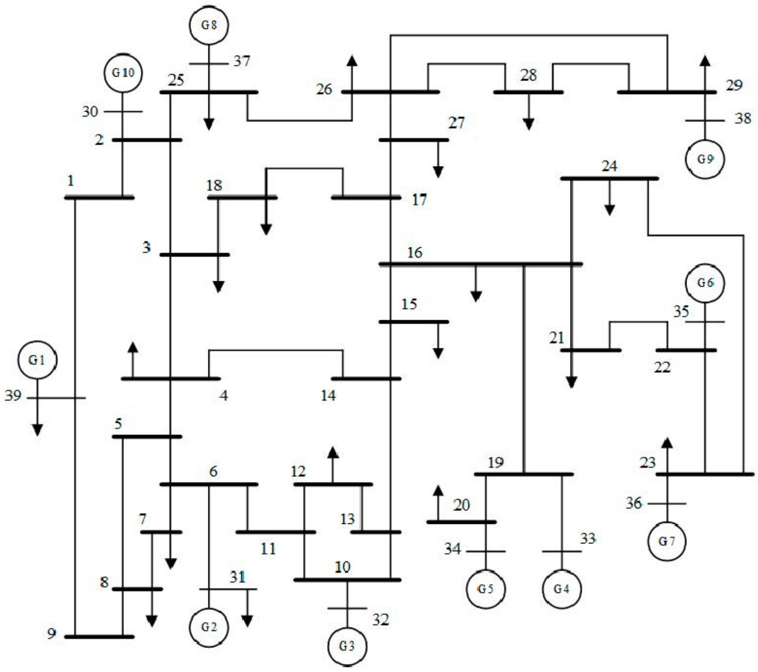
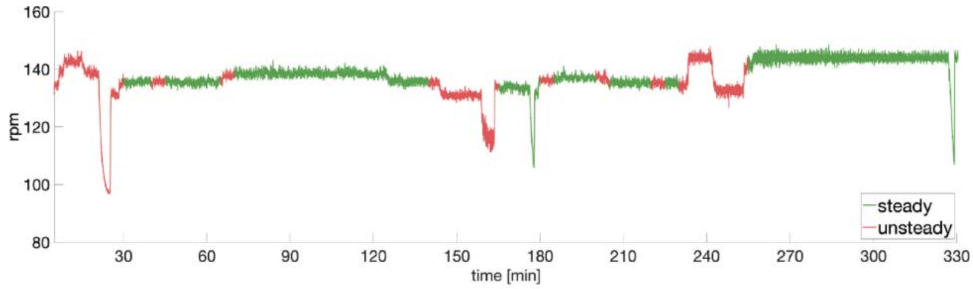


Fig. 3.1: *IEEE39 node system structure.*

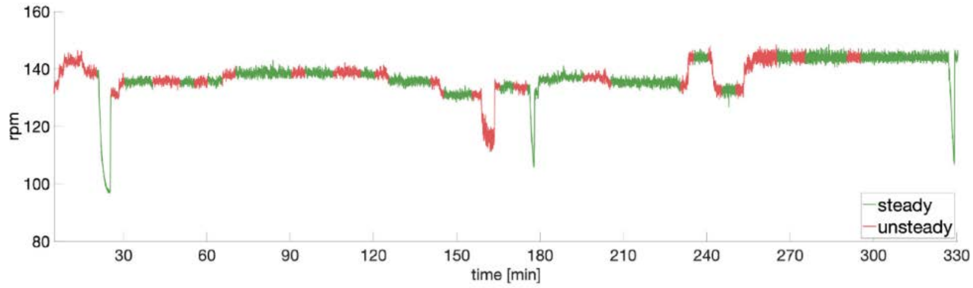
realize efficient power scheduling for the massive real-time distribution network. The signal pre-processing stage mainly includes noise removal, normalization and anomaly extraction [19]. The Kalman filter and other efficient filtering methods can suppress the noise in the signal. The standardization process ensures the consistency of data. Advanced outlier detection methods, such as isolated forests, can ensure accurate identification and elimination of possible error information. Principal component analysis, self-coding and other methods can effectively extract important information related to security situation cognition from massive videos. Because of the system's demand for persistent storage, Hadoop lays a good foundation for the efficient storage of massive data. In addition, to realize real-time data retrieval, people also developed Cassandra, MongoDB and other databases based on NoSQL to realize high-speed data retrieval. Methods such as disk array and error correction code ensure that the required data can be restored entirely after some nodes fail to ensure data integrity and consistency. In addition, the system also encrypts the data at multiple levels to ensure the confidentiality of the data. In addition, the intelligent sensing grid also contains the concept of flexible computing and storage. When the data is increased, the system can be expanded horizontally to cope with future data processing and storage problems.

3. System test.

3.1. Establishment of the test environment. The Linux Ubuntu19.04 operating system and JDK1.8 programming components are used. The test platform was built using 7 virtual institutions. The four VMSs serve as the secondary nodes of the data node. The system then consists of two hosts and one management node. There are two configurations for Hadoop users from the SSH protocol. First, the SSH protocol is installed on each virtual machine, creating a post-SSH folder. This facilitates the subsequent system guidance and instruction operation. A non-key pair encryption scheme based on SSH is proposed. The address configuration from node to host is realized through the configuration of Core components such as core-site.xml and MapReduce. The main result of this experiment is 4IEEE39 nodes. It consists of 10 units, 46 lines and 19 load nodes. The detailed topology is shown in Figure 3.1.



(a) Local steady state when first window is shifted 0 samples.



(b) Local steady state when first window is shifted 30 samples.

Fig. 3.2: *Time series data of steady-state action behavior of distribution network.*

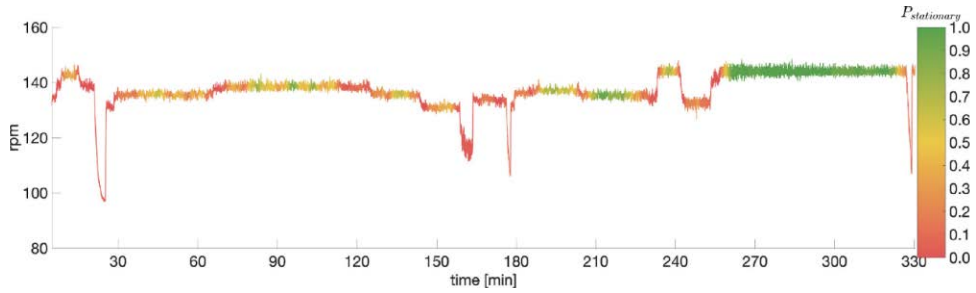


Fig. 3.3: *Line chart of perceptual results.*

3.2. Setting the parameters of the perception model. The system is correctly set before execution to improve the detection accuracy further. Nessus software was used to analyze the running state characteristics, and 200 situation time series data, as shown in Figure 3.2, were collected. The steady-state time series data is regarded as a nonlinear sequence, and the nonlinear relationship is established in the output space of each dimension to realize the perception of the steady-state operation of the distribution network. By analyzing 200 steady-state time series data and setting the dimension of the input vector to 3 and 5, 197 test samples were obtained. The data set collected above is used in the learning of neural networks. The final parameter of the algorithm is determined by comparing the deviation of each parameter with its output. Through analysis, it is found that the number of hidden layer nodes of this method can reach 20 when 5 input vector dimensions are set so that the stable operation state of the distribution network at the next moment has high accuracy.

3.3. Analysis of test results.. This method monitors the whole-day performance of the IEEE39-node system in real time and is integrated with the measured data. This results in the running effect curve shown in Figure 3.3. By comparing the measured data with the measured results, the performance of the proposed system in practical application is illustrated. The stable state values obtained by the detection system proposed in this paper mostly agree with the actual situation. Reversals occur only at 10 and 15 o 'clock. A method based on RMSE was proposed to measure the method's accuracy to make the method more vividly reflect the use efficiency. The larger the RMSE value is, the higher the detection accuracy of the method is.

RMSE refers to the square root error of the mean, n is the amount of behavior data in A stable state, i is some stable data sample, x_i is the real situation value, and $\underline{x}_i$ is the perceived situation value. According to equation (3.1), the minimum mean square error of the system in this paper is o.o31. This method can accurately detect the dynamic characteristics of the distribution network.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left|x_i - x_j\right|^2} = 0.031 \tag{3.1}$$

4. Conclusion. This project intends to adopt an adaptive sensing model based on artificial intelligence. Then the model is introduced into the reinforcement learning of each hidden node to realize real-time adjustment of the weights of each hidden node. In this way, the average value of each hidden node is less than 3.1%, which can meet the stable operation requirements of the distribution network. However, due to the limited development time, the interface of the perceptual effect display is relatively simple, which requires some beautiful design on the interface so that the user has a better experience.

REFERENCES

[1] Reebadiya, D., Rathod, T., Gupta, R., Tanwar, S., & Kumar, N. (2021). Blockchain-based secure and intelligent sensing scheme for autonomous vehicles activity tracking beyond 5g networks. Peer-to-Peer Networking and Applications, 14(5), 2757-2774.

[2] Wang, W., Lou, B., Li, X., Lou, X., Jin, N., & Yan, K. (2020). Intelligent maintenance frameworks of large-scale grid using genetic algorithm and k-mediods clustering methods. World Wide Web, 23(2), 1177-1195.

[3] Doghri, W., Saddoud, A., & Chaari Fourati, L. (2022). Cyber-physical systems for structural health monitoring: sensing technologies and intelligent computing. The Journal of Supercomputing, 78(1), 766-809.

[4] Sharma, A., & Chauhan, S. (2020). A distributed reinforcement learning based sensor node scheduling algorithm for coverage and connectivity maintenance in wireless sensor network. Wireless Networks, 26(6), 4411-4429.

[5] Kingsley-Amaehule, M., Uhunmwangho, R., Nwazor, N., & Okedu, K. E. (2022). Smart Intelligent Monitoring and Maintenance Management of Photo-voltaic Systems. International Journal of Smart Grid, 6(4), 110-122.

[6] Yu, X., Ergun, K., Cherkasova, L., & Rosing, T. Š. (2020). Optimizing sensor deployment and maintenance costs for large-scale environmental monitoring. IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, 39(11), 3918-3930.

[7] Mufana, M. W., & Ibrahim, A. (2022). Monitoring with Communication Technologies of the Smart Grid. IDOSR Journal of Applied Sciences, 7(1), 102-112.

[8] Ren, Y., Wang, T., Zhang, S., & Zhang, J. (2023). An intelligent big data collection technology based on micro mobile data centers for crowdsensing vehicular sensor network. Personal and ubiquitous computing, 27(3), 563-579.

[9] Ochuba, N. A., Usman, F. O., Okafor, E. S., Akinrinola, O., & Amoo, O. O. (2024). Predictive analytics in the maintenance and reliability of satellite telecommunications infrastructure: a conceptual review of strategies and technological advancements. Engineering Science & Technology Journal, 5(3), 704-715.

[10] Lima, A. L. D. C. D., Aranha, V. M., Carvalho, C. J. D. L., & Nascimento, E. G. S. (2021). Smart predictive maintenance for high-performance computing systems: a literature review. The Journal of Supercomputing, 77(11), 13494-13513.

[11] Serradilla, O., Zugasti, E., Rodriguez, J., & Zurutuza, U. (2022). Deep learning models for predictive maintenance: a survey, comparison, challenges and prospects. Applied Intelligence, 52(10), 10934-10964.

[12] Li, J., Gu, C., Xiang, Y., & Li, F. (2022). Edge-cloud computing systems for smart grid: state-of-the-art, architecture, and applications. Journal of Modern Power Systems and Clean Energy, 10(4), 805-817.

[13] Osunsanmi, T. O., Aigbavboa, C. O., Oke, A., & Onyia, M. E. (2022). Making a case for smart buildings in preventing corona-virus: focus on maintenance management challenges. International journal of construction management, 22(16), 3109-3118.

[14] Shcherbakov, M., & Sai, C. (2022). A hybrid deep learning framework for intelligent predictive maintenance of cyber-physical systems. ACM Transactions on Cyber-Physical Systems (TCPS), 6(2), 1-22.

[15] Yan, Y., Liu, Y., Fang, J., Lu, Y., & Jiang, X. (2021). Application status and development trends for intelligent perception of distribution network. High Voltage, 6(6), 938-954.

[16] Adekanbi, M. L. (2021). Optimization and digitization of wind farms using internet of things: A review. International Journal of Energy Research, 45(11), 15832-15838.

[17] Wang, J., Wang, X., Ma, C., & Kou, L. (2021). A survey on the development status and application prospects of knowledge graph in smart grids. IET Generation, Transmission & Distribution, 15(3), 383-407.

[18] Kong, Q., Lu, R., Yin, F., & Cui, S. (2020). Privacy-preserving continuous data collection for predictive maintenance in vehicular fog-cloud. IEEE Transactions on Intelligent Transportation Systems, 22(8), 5060-5070.

[19] Wang, F. Y., Guo, J., Bu, G., & Zhang, J. J. (2022). Mutually trustworthy human-machine knowledge automation and hybrid augmented intelligence: mechanisms and applications of cognition, management, and control for complex systems. Frontiers of Information Technology & Electronic Engineering, 23(8), 1142-1157.

Edited by: Hailong Li
Special issue on: Deep Learning in Healthcare
Received: May 31, 2024
Accepted: Jul 13, 2024